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The Impact of Monetary Policy on Volatility of Equity Returns

A VARX and HFI approach

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Abstract

This study provides evidence for a positive relationship between an unexpected monetary policy shock and volatility of equity returns. It also finds a link between the former and possible transmission mechanisms: Dividend Yield, Discount Rate, and Leverage. It combines the dynamic analysis allowed by the VARX framework suggested by Gospodinov and Jamali (2015), while obtaining the monetary shocks from the instrumental VAR with HFI estimated by Gertler and Karadi (2015), that grant exogeneity and accounts for shocks to *Forward Guidance*. It also shows how results may change drastically when using a traditional shock measurement, especially when considering the observations after the last financial crisis.

Keywords: Monetary Policy, Market Volatility; High Frequency Identification; VARX

1. Introduction

During the Great Recession, the financial markets have experienced an unprecedented turmoil. Amongst other phenomena, realized volatility of equity returns[1] raised into levels never registered before. In response to the crisis, monetary agents entered in an era of unconventional monetary policy (MP), leading their traditional instrument, the Federal Funds Rate (FFR), to zero and resorting to communication and large-scale asset purchasing programs. But have monetary policy agents the ability to affect market volatility? And if so, through which mechanisms is the effect transmitted? Is there a difference before and after the Great Recession?

Gospodinov and Jamali (2015) (GJ hereafter) have already asked the same questions. Their study uses a monthly VARX framework with data comprised between 1990 and 2008. They defined the shocks as the unexpected shift on MP, gauging the market expectation through the implied rate on the 30-day Federal Funds Rate Futures and compared it with the actual average Federal Funds Target Rate (FFTR) at the future's maturity. They have noted that, an unexpected MP hawkish shock caused an increase in volatility, essentially transmitted by the persistent effect on the Dividend Yield. In their conclusions it was suggested that, after 2008, the gap between the expected and the actual target interest rate was to be close to zero, which would diminish the effect of MP on volatility. Their reasoning was as follows: since monetary agents started heavily relying on communication to increase transparency, the predictive capability of market agents was consequently improved, which makes surprises less likely to occur. This communication is referred by the authors as *Forward Guidance*.

So, to test the ability of monetary agents to influence market volatility, a correct measurement of a MP shock is needed. Indeed, the literature has found evidence for the importance

[1] For the sake of simplicity, market volatility or simply volatility will always refer to volatility of equity returns

of unexpected shocks as opposed to expected ones. (e.g. Bomfim, 2003 ; Bernanke and Kuttner, 2004). Besides that, two main problems occur with the MP shock series construction proposed by GJ. The first is that the FFTR was discontinued in 2008, which makes expanding the sample potentially troublesome. Furthermore, there is no guarantee that the change in the FFTR is completely exogenous[2]. The second problem is concerned with the definition and measurement of *Forward Guidance*. Indeed, communication may help market participants to make a better assessment of monetary agents' future actions, but this is only one of the applications of *Forward Guidance*. Communication can shift the expected path of future short-term interest rate. Through this, monetary agents can influence a diverse number of asset prices, even if the FFR is virtually zero. So much so that Swanson and Williams (2012) and Wu (2016) showed that the yields of fixed income assets continued extremely responsive to MP after 2008, unbounded by the apparent zero lower bound.

Hence, a correct measurement of a MP shock should 1) measure unexpected shocks, 2) account for effects of unconventional actions and 3) be exogenous to the model. We find that the High Frequency Identification (HFI) literature fulfills these requirements. This method also gauges market expectations using short-term interest rate futures[3], and measures their variation in a tight window around a significant monetary event (usually 30 to 60 minutes), most commonly the Federal Open Market Committee (FOMC) statement release. Since expectations are gauged using futures, 1) is guaranteed. If the futures used are expiring in any month other than the current one, it captures consensus on longer term interest rates, granting 2). Finally, the tight window restriction makes it extremely unlikely for expectations to be reacting to any type of non-monetary news, or for monetary agents to be reacting to the economy, avoiding simultaneity and omitted variable bias,

[2] monetary agents could, for example, be reacting to information present in the model
[3] such as the 30-day Fed Funds Rate or Eurodollar Futures

which circumvents endogeneity (3)).

This thesis aims to build upon the work of GJ by including a MP series that accounts for the most recent developments in the literature, while still providing clear evidence to the possible misleading results that could be taken otherwise. For this, we use GJ's VARX framework and compare the results using two different series as MP measurement. The first one is similar to the original, but instead of using the discontinued FFTR series, uses the Effective Fed Funds Rate (EFFR). Granted, it will potentially increase endogeneity as the EFFR is not completely controlled by the Fed, thus making it exposed to other non-monetary factors, such as risk-aversion changes. But one can also argue that the Fed might stray from the stated Target Rate in times of need, which is reflected in the EFFR. Nonetheless, the usage of this series is exactly to show how misleading the results might be if the MP estimation method is flawed. The rest of the paper will refer this series as FEDS. The second one extracts the series from the 6-variable instrumental VAR with High Frequency Identification (HFI), developed by Gertler and Karadi (2015) that comprises the period between 1991m1 and 2012m6.

Our results have shown that prior to the financial crisis, both estimation methods yielded similar results, whereas taking the full sample into consideration, everything changes. When using the FEDS series, the Dividend Yield effect has disappeared, but more surprisingly the effect of a hawkish shock translated into a decrease on volatility, contradicting the results of GJ. But if one would use the HFI series, the predictions would become much closer to the original. This shows that in times of unconventional policy, unconventional measurement tools are necessary and that monetary agents still have influence over market volatility.

The rest of the assignment will be divided into 5 parts. The second section will review the most recent literature linking monetary policy and market volatility, discussing possible transmission mechanisms as in Gospodinov and Jamali (2015). In the third section, several monetary policy identification methods will be reviewed. The fourth part will display the methodology and the data included in the model. The fifth section will present the results and discussion. The final part will give the main takeaways.

2. Equity Market Volatility

2.1. Linking Monetary Policy and Market Volatility

The financial markets for equities have for a long time played a relevant role in the monetary policy literature. Several empirical works have found that an unexpected policy tightening results on lower excess equity returns (see for example Thorbeke, 1997 ; Bernanke and Kutner, 2004)).

The latter have tried to explain this relationship by measuring the shocks on the real interest rate, on expected returns and on dividends. They have surprisingly found that real interest rates were not playing a significant role. They suggested that this effect could be attributed to the direct increased risk of the firm, that given an interest rate hike would see its balance sheet deteriorate. A second reason provided was related to the investor’s increased unwillingness to hold risk due to possible future higher inflation or decreased level of consumption, signaled by an interest rate hike. Therefore, investors will demand higher returns (premium), decreasing current stocks’ prices.

These two possible explanations may bridge shocks in monetary policy and the two major theories that seek to explain the well-known negative relationship between stock returns and future volatility: The Leverage Effect and the Volatility Feedback Hypothesis.

Introduced by Black (1976) and Christie (1982), the Leverage Effect states that a decrease of a firm’s stock price will lead to a higher leverage ratio. Like the first explanation provided by Bernanke and Kutner (2004), this deterioration of the firm’s financial situation will lead to an increased business riskiness which would eventually translate into price volatility in the future.

The second main theory reverts the causality of the effect. If the Leverage Effect postulates that the decrease in returns translates into an increased future expected volatility, in the Volatility

Feedback Hypothesis (Campbell and Hentschel, 1992) is the expected future volatility that translates into the current stock returns. If future volatility is expected to be higher, investors will find themselves with riskier assets in hands, demanding increased future returns. For this to happen, current prices should decrease. This theory assumes that investors demand a premium for risk, that future volatility is indeed priced, and this compensation changes overtime. Furthermore, Campbell and Hentschel (1992) have also postulated that news can also increase volatility. According to their findings, big news will always have more (smaller) news associated to them in the future.

Similar to Bernanke and Kutner (2004), GJ have also considered the Dividends and the Discount Rate as possible transmission mechanism. They state that an unexpected tightening will increase the Discount Rate, which will make Future Cash Flows (Dividends) more uncertain.

2.2. Previous Work

Asset volatility has been used for the most diverse purposes, including asset pricing and risk management. It is no surprise that links between monetary policy and volatility have been often studied in the literature. The most common procedures in the literature consist in using Garch-type models at a daily or even intraday level. Some examples follow below.

Using an exponential Garch (EGarch) and gauging market expectations through survey methods, Lobo (2002) has discovered that volatility increases in the day of the announcement of an unexpected rate change, but quickly reverts to pre-announcement levels at the following day. He also found an asymmetric relationship between news and volatility, more specifically, unexpected interest rate hikes (bad news) yield increased volatility.

Bomfim (2003) has used a Garch(1,1) to test whether the *calm-before-the storm* effect exists and the impact of the decision itself on market volatility. He uses future-based measures to extract market participants expectations, being able to measure the surprise by comparing it to the announced target rate. He found evidence that after 1994, the days prior to the FOMC announcement present abnormally low volatility, whereas the day itself presents higher volatility. He also noted that unexpected changes in interest rates have a substantial impact on the FOMC day and produce an asymmetric effect. Using a High Frequency Identification method, Farka (2009) found similar results at an intraday level, as well as asymmetries, such as interest rate hikes having a higher impact on volatility than eases, higher impact on volatility when the economy is facing an economic slowdown and stating that path shocks dominate timing ones.

Even if extremely useful to test some short-term relationships, Garch-type approaches lack the capability to study the persistence of the impact and which mechanisms transmit the shock. The work of Gospodinov and Jamali (2015) provides a plausible solution by using a monthly VARX framework. They have studied the reaction of excess returns and volatility as well as possible transmission channels (Dividend Yield, Leverage, Volatility Feedback, Discount rates and Volume[4]) to a contractionary policy shock (which was considered the exogenous variable). They have gauged market expectations by using the one-month ahead implied 30-days Federal Funds Rate futures at the last day of the month and comparing it with the average of the FFTR in the following month. The difference is considered as the unexpected shock. The time sample used was between 1990m1 and 2008m12. Their conclusions will be further discussed ahead.

3. Measuring Monetary Policy Shocks

3.1.Theoretical Background

The first step to measure a monetary policy shock is its definition. To avoid spurious results, it should be noticed that not only other economic variables react to monetary policy actions, but also the other way around. This simultaneity can severely bias the results. Following Christiano, Eichenbaum, and Evans (1999), this endogenous reaction is called the *Feedback Rule* (or reaction

[4] Also known as *News Channel*

function) and the difference between it and the policy indicator is the exogenous shock:

$$Y_t^p = f(\Omega) + \varepsilon_t^p \tag{1}$$

Where Y_t^p is a monetary policy indicator, $f(\Omega)$ is the reaction function to a set of variables Ω and ε_t^p is the exogenous shock. The key is therefore to estimate either $f(\Omega)$ or ε_t^p directly.

Even though it is a relatively simple concept, its empirical application may be particularly troublesome. First, finding a pure policy indicator may turn out to be an arduous task. As already noted, if one would consider the FFR as an indicator, he would fail to measure effects of *Forward Guidance*. Furthermore, the FFR is set between banks, and not directly controlled by the Fed, which means that part of its variation can be attributed to non-monetary factors, such as term premiums variations. Using assets with longer maturities will only increase the reactions to other types of non-monetary news. Still related with the indicator selection, identifying all the news to which monetary policy is reacting may also be close to impossible. If there is a given event or variable that causes a reaction of monetary agents and other variables included in the model, then it is certain that an omitted variable bias exists. Gurkaynak, Sack, and Swanson (2004) consider employment releases to be a good example of this.

The second set of problems relates with foresight. Ever since the Lucas Critique, expectations have plaid a huge roll in the literature. According to Ramey in his chapter in Taylor and Uhlig (2016), both the Fed and the market participants move according to their expectations about the future, using all the available information at the time. The same author notes that the Fed is known to use a huge amount of information[5] that may be very difficult to quantify. Not accounting for that may consequently bias the results[6]. As the previous example, by incorrectly

[5] Some of it may even be private
[6] For instance, if the Fed forecasts that the economy may overheat in the future, he will react by increasing the interest rates

measuring the reaction of monetary policy to GDP, the relationship becomes spurious. Finally, market participants also form their expectations about the future using all the available information to do so. This said, asset prices already reflect those expectations, which means that they will only react if those expectations are not met. Therefore, an interest rate move by the Fed may not cause asset prices to react if it is anticipated whereas leaving the rates unchanged may cause a reaction if it is not anticipated.

Concluding, a correct measurement of monetary policy should separate what is a simultaneous response of monetary agents and economic variables as well as accounting for omitted variables in the data. It is also important to choose a policy indicator that correctly captures *Forward Guidance* and finds the share of its variation that is related with monetary actions only and with no other types of news. Finally, this reaction should reflect a shock to expectations and account for possible asymmetric information between agents.

3.2. Empirical Work

Due to its importance, the literature about monetary policy measurement is vast. As hinted before, to estimate a monetary policy shock it is necessary to estimate $f(\Omega)$, ε_t^p, or even both simultaneously. One of the most straightforward methods is to assume a rule for $f(\Omega)$, such a Taylor-type rule. Another popular econometrical framework used is the SVAR approach, with different kinds of identification strategies (see for instance Christiano, Eichenbaum, and Evans, 1999; Romer and Romer, 2004; Bernanke, Boivin, and Eliasz, 2005) . By including Y_t^p in a system with other variables, the traditional SVAR approach assumes that $f(\Omega)$ can be estimated using the lags of all the variables present in the model and some contemporaneous restrictions, usually recursive as in Christiano, Eichenbaum, and Evans (1999). This can be problematic not only since the Fed may be using information not contained in the lags of the variables included in the model, but also contemporaneous restrictions may be implausible in some situations where price stickiness does not exist, such as in financial variables.

Some have suggested a solution to these problems[7]. Unfortunately, the most common methods usually use a recursive identification strategy, which is not plausible when financial variables are present.

Gertler and Karadi (2015) combine High Frequency and VAR literature. Following the HFI literature (Bernanke and Kuttner, 2004; Gurkaynak et al., 2004; Gertler and Karadi, 2015), the authors use implied rates on short-term interest rate futures to gauge market expectations. This method argues that short-term interest rate futures efficiently reflect both the expectations on future path of short-term interest rates and a risk premium. Thus, price changes are either a consequence of revisions of the future rate path or risk premium changes. The objective is to isolate the portion of the price change that is caused by a monetary event. The method proposed by the HFI literature is to restrict the change's measurement around a relevant monetary event in a tight window (usually 30 to 60 minutes) after an FOMC announcement. Intuitively, this narrow period makes highly unlikely for markets to be reacting to other news or risk premium granting exogeneity (Gertler and Karadi, 2015).

If the HFI literature usually considers this variation as a pure measurement of the shock itself, Gertler and Karadi (2015) differ by considering that they are only correlated with the shock itself (ε_t^p) and nothing else, making it a valid instrument in a VAR framework. They then proceed to choose a policy indicator (Y_t^p), usually the 1 or 2-year T-Bond yield, and use this High Frequency estimates to measure how much of the variation of the prior is explained by the unexpected shock.

[7] For instance, Romer and Romer (2004) included a series which accounted for Fed's intention in each action as well as the forecasts provided in the FOMC report, also known as Greenbook Forecasts. Bernanke, Boivin, and Eliasz (2005) have augmented the typical VAR using Dynamic Factor Analysis, increasing the amount of information used in a VAR while still avoiding the dimensionality curse

In this way, they can attribute part of the residual variation of Y_t^p due to unexpected shocks, yielding a true quantification of ε_t^p . Their method is particularly useful due to its usage of external information to circumvent time-restrictions and including extra information in the model, gauging expectations in the market, avoiding endogeneity and capturing shocks to *Forward Guidance*.

4. Methodology

The procedure used is two-phased. The first phase estimates exogenous shocks to monetary policy. For the sake of comparison, two series are extracted. One is similar (but slightly different) to GJ and the other is the one estimated by (Gertler and Karadi 2015) (GK). Finally, both series will be taken as exogenous variables in the VARX framework proposed by (Gospodinov and Jamali 2015). Since the first step is only the measurement procedure for one of the variables in the VARX (the exogenous one), it was found more appropriate to first outlay the latter, whereas the initial phase will be explained in the "Data" section.

4.1. VARX

We follow a Vector Autoregressive approach with an exogenous (more specifically a VARX(p,q)) variable as follows:

$$Y_t = \sum_{j=1}^{p} A_j Y_{t-j} + \sum_{i=0}^{q} \Phi_i MP_{t-i} + u_t \tag{2}$$

Where MP_t and Y_t are the sets of exogenous and endogenous variable sets respectively. The latter includes excess returns and volatility measure as well as possible transmission mechanisms, more specifically the Leverage, Volatility Risk Premium, Dividend Yield, Volume and Discount Rates used by GJ. The former will include one exogenous policy shock estimator. We will then compare an adapted version of the one used by GJ and by GK. Further explanations of the variables are present in the next section. The number of lags is selected using the Akaike Information Criteria.

4.2. Data

This subsection is divided into two parts. The first one outlays a brief description of the endogenous dataset. Since their calculation follows GJ, we will not present too much detail. Indeed, the data was taken from different sources as GJ. Instead of using *Yahoo! Finance* and the *CME group*, the data is extracted from a *Bloomberg* terminal and the *FRED* database. This may cause discrepancies from GJ, especially regarding data related to futures.

The second part will carefully explain the two approaches used to calculate the monetary policy series. The methods are based off GJ and GK. Finally, the sample is constrained to the data available. Since the HFI data provided for GK only covers the time span between 1991m1 and 2012m6, the data was collected for this period.

4.2.1 Endogenous Variables

The endogenous variables present in the model are monthly proxies for excess returns and volatility as well as the possible channels. Following GJ the channels will be the Dividend, Leverage, Volatility Feedback, Discount rate and Volume.

The excess returns are the monthly log returns on the S&P500, subtracted by the three-month T-bill. Volatility is proxied by the month's realized volatility as in Bandi and Perron (2006). The Volatility Feedback is measured using Volatility Risk Premium, as measured by the difference between the risk neutral and physical volatility, that is, the difference between the VIX index and realized volatility. The Dividend Yield is the 12-month average dividend yield on the S&P500. The discount rate is proxied by two variables: the real interest rate which is the three-month T-bill minus the inflation (as measured by the CPI) and the difference of the T-bill also uses the previous T-bill. The leverage proxy is the growth rate on the Commercial and Industrial Loans, All Commercial Banks series from FRED and Volume is the unexpected trading volume on S&P 500 futures, proxied by the residuals of an AR(10).[8]

4.2.2. Exogenous variables – Monetary Policy Shock

Monthly Future Based Measure (FEDS)

The 30-day federal funds futures are traded securities that derive their value from the average FFR at the maturity month[9]. Their high responsiveness to monetary policy has made this type of assets particular useful to gauge market expectations (e.g. (Kuttner 2001)). The construction used by GJ uses these assets to measure the market consensus about the average FFR during any given month. They do so by using the implied federal funds future rate (FFFR) at the last trading day of the previous month's one-month ahead FFF. Having a measure of these expectations, the following step is the comparison between them and the actual average FFR, more specifically the discontinued average federal funds rate target (FFTR).

To extend the sample size, we have opted to use the average effective federal funds rate (EFFR). Indeed, this change will certainly increase endogeneity in the model. Furthermore, and as noted by Kuttner (2001), at a daily level the series might have significant differences from one another, but those are practically inexistent at a monthly level. The series is therefore:

$$\widehat{\varepsilon_t^p} = FFFR_{t-1}^1 - EFFR_t \tag{3}$$

Where ε_t^p is the monetary policy shock of month t, $FFFR_{t-1}^1$ is the closing one-month ahead FFFR from the previous month (t-1) and $EFFT_t$ is the average effective FFR at month t.

Instrumental VAR with HFI (HFI)

Gertler and Karadi (2015) take the following structural VAR model:

$$DX_t = \sum_{j=1}^{p} C_j X_{t-j} + \varepsilon_t \tag{4}$$

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[8] Please consult appendix 1 for the variable's first two centered moments and first-order autocorrelation

[9] More specifically $FFF = 100 - r$, where r is the average of the FFR at the expiration month

Where X_t is a vector with all the variables at time and ε_t a vector of all the structural shocks. Let us set $X_t^p \epsilon X_t$ the policy indicator with an associated structural shock ε_t^p and $D^{-1} = S$. Multiplying both sides by S will yield the reduce form VAR:

$$X_t = \sum_{j=1}^{p} B_j X_{t-j} + e_t \tag{5}$$

Where $e_t = S\varepsilon_t$, $B_j = SC_j$ and $E[e_t e_t{}'] = E[SS'] = \Sigma$, where Σ is the variance covariance matrix.

Since we only want the elements of the column of **S** associated with the shock, ε_t^p needs to be estimated. Let us name it **s.** Thus, the estimated model will be:

$$X_t = \sum_{j=1}^{p} B_j X_{t-j} + s\varepsilon_t \tag{6}$$

The next step is to impose restrictions to the model. As previously stated, when using financial variables, recursive restrictions are not possible. This procedure circumvents this problem by assuming that the instrumental set Z_t is correlated to ε_t^p but uncorrelated to ε_t^q, for any $p \neq q$. This is the same to say that the future data collected after the FOMC announcement is only reacting to the monetary event, which is plausible.

After imposing these restrictions, it follows a two-stage regression. Similar do the 2SLS, the first step regresses the residuals of the policy indicator on the instrumental set:

$$e_t^p = \alpha + \beta Z_t + \omega_t \tag{7}$$

This step isolates the variation on e_t^p exclusively associated to ε_t^p. Hence the fitted value $\widehat{e_t^p}$ can be interpret as:

$$\widehat{e_t^p} = \widehat{s_t^p \varepsilon_t^p} \tag{8}$$

So, the following step is the estimate s_t^p. This can be done by using the Σ matrix and the following equation estimate. [10]

$$e_t^p = \frac{s^q}{s^p}\widehat{e_t^p} + \xi_t \tag{9}$$

Having s^p estimated, $\widehat{\varepsilon_t^p}$ can be promptly extracted from $\widehat{e_t^p}$

Finally, the variables present in X_t are the one-year government bond rate (as the policy indicator), the log consumer price index, the log industrial production, the mortgage spread, the commercial paper spread and the excess bond premium as measured by Gilchrist and Zakrajšek (2012). The instrumental variable Z_t uses the 30 minutes high frequency set of the three-month ahead FFFR. By using both a policy indicator and instrumental variables with longer maturity, this method is able to capture shocks to *Forward Guidance*.

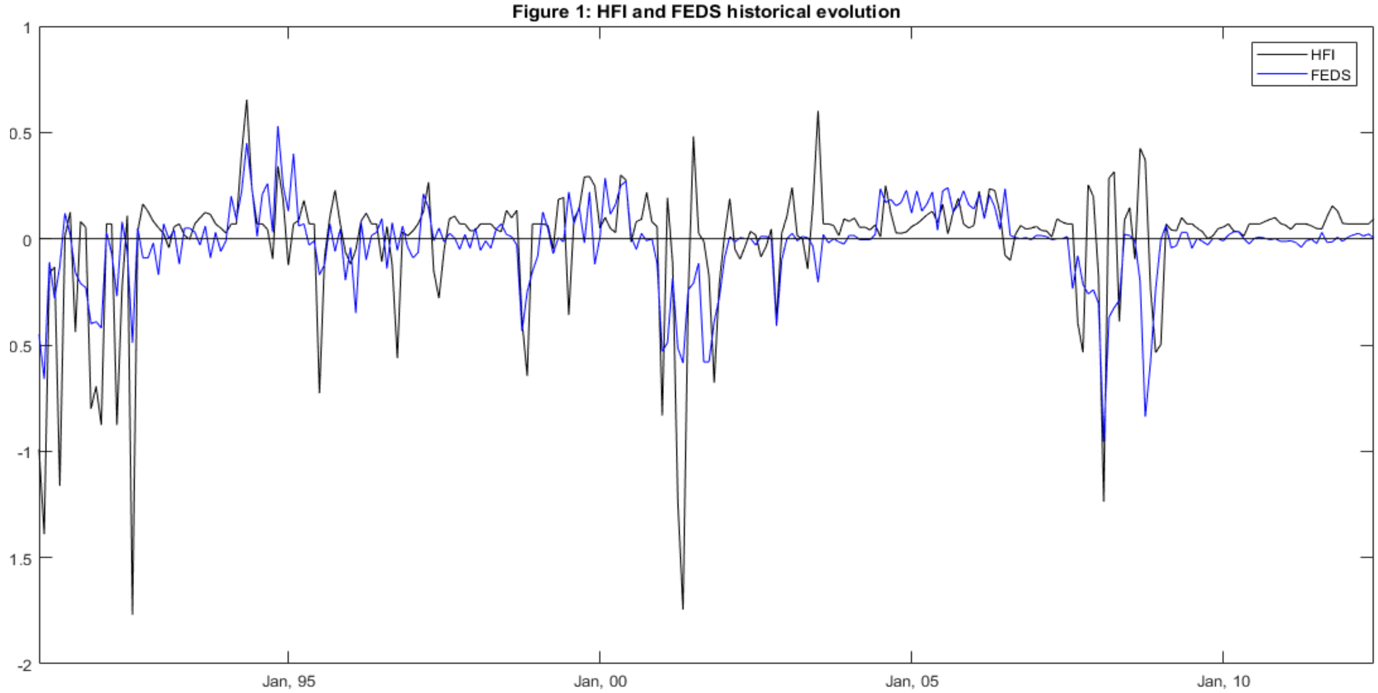
5. Results

5.1 Comparing both MP series

With a 0.57 correlation coefficient, both series are substantially different and have distinguishable traits. For starters, both the mean and standard deviation are clearly different. Even though the HFI is more volatile, having a standard deviation of 0.31 as opposed to 0.20, both HFI and FEDS processes produce on average negative shocks, although the latter having on average more negative results (-0.03 as opposed to -0.01 p.p.). The higher volatility should reflect the wider level of expectations captured by the HFI, whereas the more negative mean in the FEDS series may be caused by some possible reaction to economic downturns by the Fed that is not correctly measured by the FEDS series.

[10] The authors suggest consulting the original paper for a full derivation

Figure 1: HFI and FEDS historical evolution



Looking at both series' plots, it not only appears that HFI is more volatile, but also that the shocks usually have a greater scale. It is also interesting to notice the changes before and after the great recession. If prior to the financial crisis the correlation coefficient was 0.63, afterwards it decreased to a mere 0.41. This may come as no surprise since prior to the zero lower bound, the Fed was able to use both the short-term interest rate and communication to affect the markets whereas afterwards it was mainly capable to use communication. As the FEDS series only capture conventional mechanisms and HFI captures both, it is natural by construction that the correlation coefficient decreases, and that the FEDS series measures a smaller portion of the shock

Furthermore, the HFI is consistently above zero (after 2008), whereas FEDS is virtually zero. This confirms the predictions made by GJ that the market participants were able to better assess the next month's EFFR, hardly being surprised by actions made by the Fed. However, the positive values of the HFI series also hints that by considering unconventional MP, the Fed is still capable of surprising the market as noted by Swanson and Williams (2012) and Wu (2016).

5.2. Dynamic Multiplier Analysis

The next step is to analyze the responsiveness of the endogenous variables to a shock on the exogenous variables. This shock is a 10-basis points surprise hike and the confidence bands are at a 95% percent level. The impulse response plots can be consulted in the Appendix: Appendix 2 and 3 measure the reaction to the shock on the pre-crisis sample (1991m1-2007m12) for the FEDS and HFI series respectively whereas Appendix 4 and 5 graph the reaction for the full sample (1991m1-2012m6).

5.2.1 Pre-Crisis Sample

Even if the response to a shock of the FEDS series appears to be of higher magnitude, the results are remarkably similar at a pre-financial crisis level. As expected, excess returns decrease contemporaneously with an interest rate hike. However, in both series there are positive excess returns on the following month, which dissipate after that. Volatility does not appear to respond to the hike with either shock series, which contradicts the hypothesis postulated by this paper. The Dividend Yield is also clearly positive affected by the shock using both series, dying out at around three months after the shock. Leverage also increases even if it is only significant some months after the shock (3 months in the FEDS and 7 with the HFI series). The main difference arises when measuring the Volatility Risk Premium, that only increases (contemporaneously) using the HFI shock. The two proxies considered as the Discount Rate mechanism, present different results from one another. The 3-month T-bill, has a higher contemporaneous increase whereas the Real Interest Rate is not significant. Finally, unexpected Volume does not appear to be a significant transmission mechanism.

5.2.2. Full Sample

When the full sample is used, huge changes appear between both series. Excess returns continue to react negatively when using HFI, but this well-documented result does not exist when using FEDS as it ceases to be statistically significant. Furthermore, volatility is significant in both scenarios but with different signs. As expected, volatility increases when using the HFI series but decreases when using the FEDS series. Furthermore, the Dividend Yield turns insignificant when using the latter series whereas the impact appears to be stronger as in the previous sample with the HFI. Interestingly, the Volatility Risk Premium is not statistically significant in either series whereas the Leverage variable continues to be significant in both (at a 3-month horizon). Another puzzling result using the FEDS series is related with the Real Interest Rate series, that reacts negatively with a policy tightening. Using the HFI series, the non-significant results are maintained. The 3-month T-bill and the Volume variables present similar responses as in the previous sample.

5.3. Discussion

GJ predict that all channels (Leverage, Dividend, Discount Rate, Volatility Feedback and Volume) contribute to the increase in market volatility. Our results are slightly different: In a pre-crisis sample level, there is no effect on volatility. When the channels are considered, only the Dividend Yield and the Volatility Feedback appear to have similar results. The Discount mechanism can also be considered partially important, as only the 3-month T-bill increases. Finally, one can also argue that the Leverage mechanism contributes, but it is only significative 7 months after the shock. Considering all the observations, volatility is positively affected one month after the shock. But in this case, the Volatility Feedback ceases to be a significant mechanism. The other variables exhibit similar results.

In this period, there is a decrease on contemporaneous excess returns which is consistent with the literature. However, volatility is not affected at a monthly level, differing from the results obtained by GJ[11]. First and foremost, due to the decrease in stock prices, the Dividend channel

[11] This can be a consequence of the different sources from which the data was obtained, and the change of the MPS series as previously explained. For what is the author's understanding, it appears that the data on futures taken

appears to have the most persistent effect, as in GJ. This reaction may be cause by the unwillingness for firms to diminish dividend payout to avoid sending bad signs to the market or losing potential clientele. Discount Rates also increase contemporaneously, which makes them into another possible explanation. However, and has noted by Bernanke and Kuttner (2004), the real interest rate does not react significantly. The Leverage Effect also appears to be present, but only a couple of months into the future, which may deem it irrelevant. Finally, the Feedback Hypothesis as measured by the Volatility Risk Premium only appears to be relevant when using HFI as an indicator. The *News Channel* as measured by the unexpected volume of the S&P futures, is not significant in any of the series.

When it comes to the full-sample however, everything changes. First, the well-documented in literature decrease on excess returns disappears when using the FEDS series, while the contemporaneous volatility responds by decreasing. When using the HFI series, the former variable maintains the current decaying behavior whereas the volatility even increases a month into the future. This may be a result of disregarding both shocks to *Forward Guidance* and the reaction component. The two months following the collapse of the Lehman Brothers in September of 2008 registered the peak of volatility in sample (79.24 and 69.41 for October and November respectively). During that time, the monetary shock as measured by the FEDS has also had two of its biggest decreases (-0.84 and -0.58 percent). If the latter shock captures macroeconomic phenomena (such as some sort of flight to safety) or a reaction of monetary policy, it is highly likely that the results to be spurious. When using the HFI series, the shocks are considerably different with 0.37 and -0.23 percent for October and November respectively. Furthermore, and as presented previously, the latter years of the sample show a consistent gap between the HFI and the

from Bloomberg may not be as reliable as the one purchased from the CME group itself. The usage of the EFFR as opposed to the Target Rate may also increase endogeneity

FEDS. If this gap is containing shocks to *Forward Guidance*, the FEDS series is not able to capture it and thus not noting an effect that might be happening.

Finally, the transmission channels hinted by both series are also different. For the FEDS, the only two that remain significant are the Leverage Effect and the discount channel. Interestingly, there is a contemporaneous decrease in the real interest rate followed by an increase on the 3rd month after the shock. Except for the Feedback Channel, when using the HFI series, the results are robust for the other transmission channels.

6. Conclusion

By using the most recent developments on MP identification, this paper has shown that monetary agents still have the ability to influence market volatility of equity returns at a monthly level, through the Leverage, Discount Rate and (essentially) the Dividend Yield. Contrary to GJ, there is no evidence for any impact prior to the financial crisis.

It has also exposed limitations of traditional monetary policy shocks measurements, which may provide considerably different results. More specifically, the inability to capture shocks to *Forward Guidance* and possible endogeneity issues may seriously skew the results. For instance, volatility responded negatively when using the FEDS series, whereas positively with a hike on HFI. The channels were also different, with the Leverage and Discount Rates being the ones present in the former whereas the Dividend Yield, Leverage and Discount channels are identified in the latter. But when considering a pre-financial crisis world, the results using both series are remarkably similar, with neither being able to find a link between volatility and monetary policy.

However, even if it can link monetary policy and volatility, the method used is incapable of directly linking the previous channels to the increase of volatility. It only measures if MP affect the specific transmission variables and relies on the literature to assume that they could translate into volatility itself. Investigation on this regard may be a future course of action.

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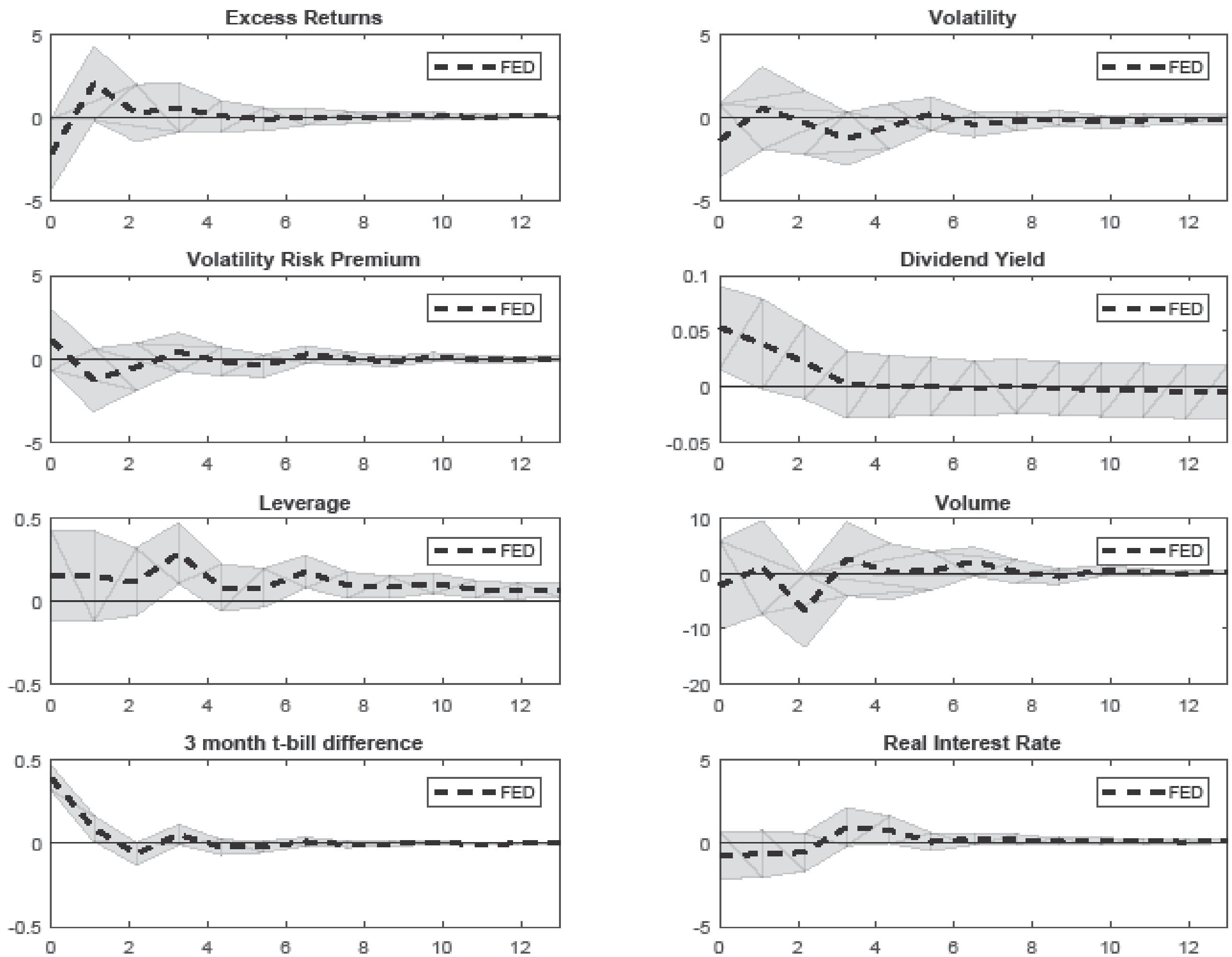
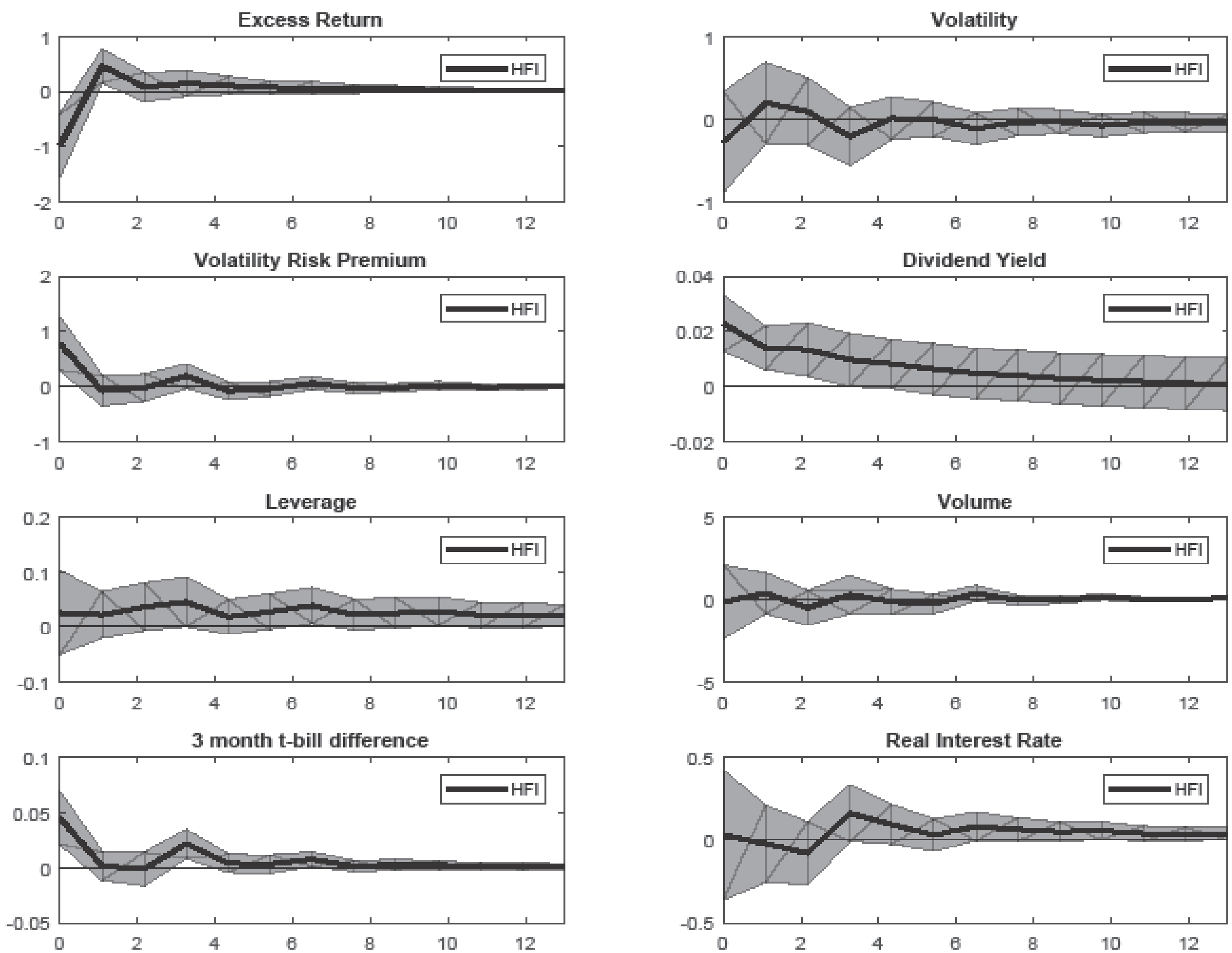
Appendix

Variable	Mean	Std. Deviation	Autocorrelation
A:1991m1:2007m12			
Excess Returns on the S&P500 (ER)	0.40	3.87	-0.06
Realized Volatility of S&P 500 (VOL)	13.92	6.52	0.71
Volatility Risk Premium (VRP)	4.78	3.40	0.13
Real Interest Rate (RINT)	1.32	2.91	0.41
Change in 3-month T-bill Rate (DTB)	-0.02	0.21	0.43
Dividend Yield on the S&P500 (DY)	1.96	0.62	0.98
Unexpected change in S&P500 futures trading volume (VOLUME)	1.27	15.54	-0.00
Commercial and industrial loan Growth (LEV)	0.39	0.82	0.71
Monetary Policy Shock - FEDS	-0.02	0.19	0.59
Monetary Policy Shock - HFI	-0.02	0.33	0.32
B:1991m1:2012m6			
Excess Returns on the S&P500 (ER)	0.28	4.37	0.06
Realized Volatility of S&P 500 (VOL)	15.72	9.55	0.77
Volatility Risk Premium (VRP)	4.65	4.56	0.24
Real Interest Rate (RINT)	0.76	3.56	0.52
Change in 3-month T-bill Rate (DTB)	-0.03	0.21	0.44
Dividend Yield on the S&P500 (DY)	2.03	0.61	0.98
Unexpected change in S&P500 futures trading volume (VOLUME)	-0.01	18.10	0.00
Commercial and industrial loan Growth (LEV)	0.30	0.95	0.74
Monetary Policy Shock - FEDS	-0.03	0.19	0.61
Monetary Policy Shock - HFI	-0.01	0.31	0.30

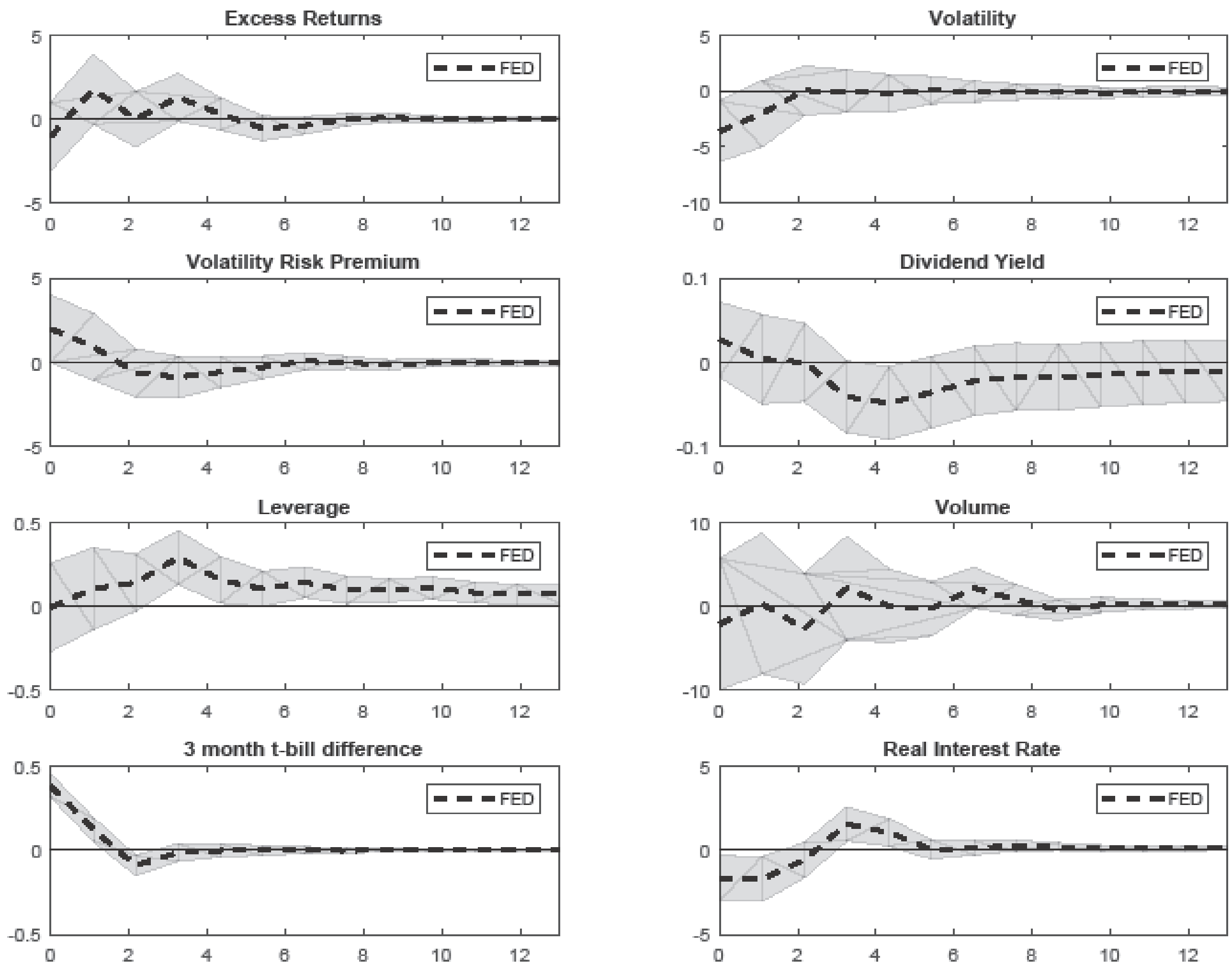
***Appendix 1** - Mean, Standard Deviation and first-order Autocorrelation of the variables present in the VARX as in Gospodinov and Jamali (2015)*



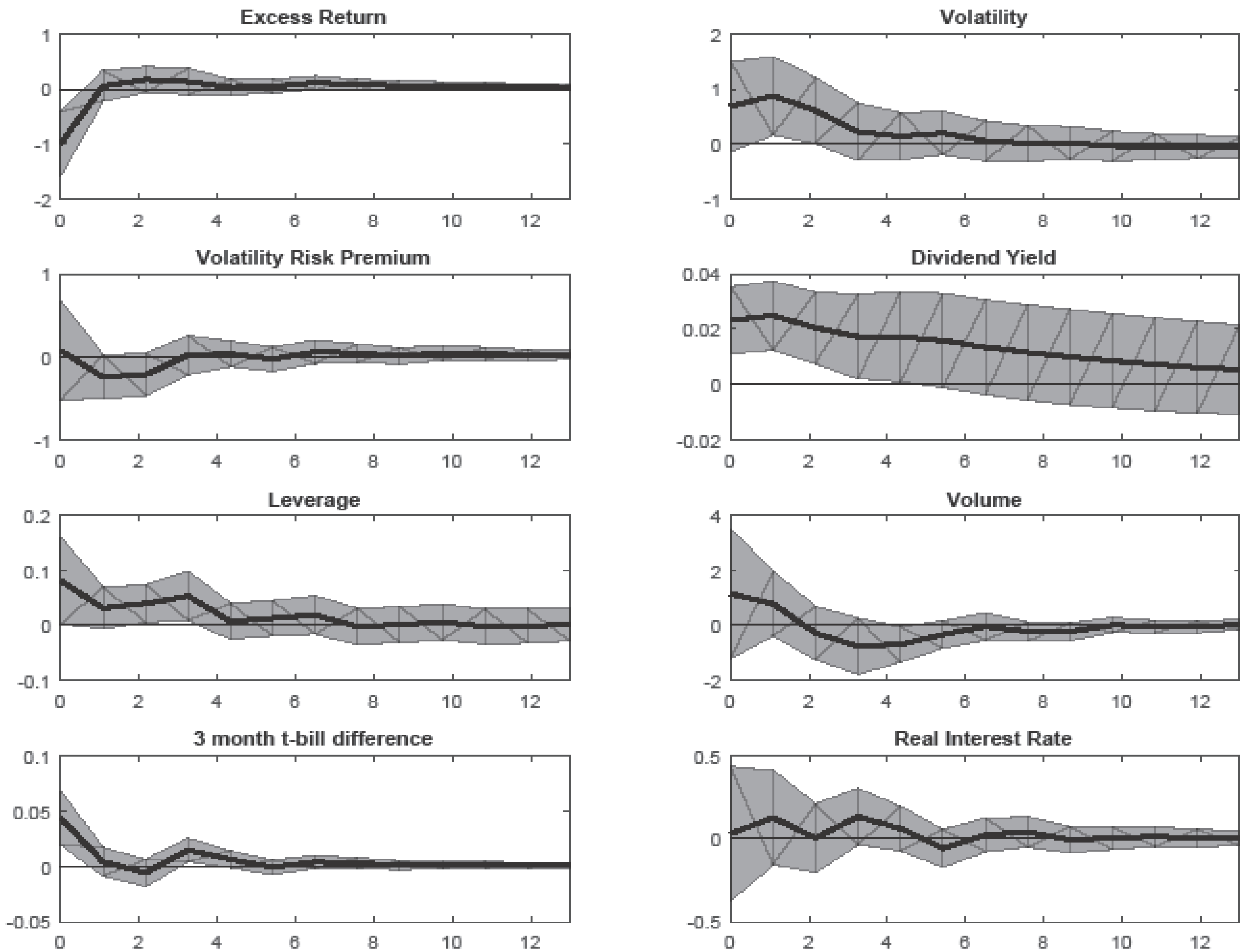
Appendix 2 *- Response to a 10-bps hike as measured by the FEDS. 1991m1-2007m12*



Appendix 3 *- Response to a 10-bps hike as measured by the HFI. 1991m1-2007m12*



Appendix 4 *- Response to a 10-bps hike as measured by the FEDS. 1991m1-2012m6*



Appendix 5 *- Response to a 10-bps hike as measured by the HFI. 1991m1-2012m6*